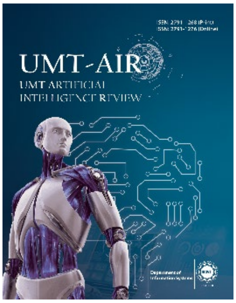

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Comparison of the Predictive Models of Human Activity Recognition (HAR) in Smartphones

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ABSTRACT: This report compared the performance of different classification algorithms such as decision tree, K-Nearest Neighbour (KNN), logistic regression, Support Vector Machine (SVM) and random forest. Dataset comprised smartphones' accelerometer and gyroscope readings of the participants while performing different activities, such as walking, walking downstairs, walking upstairs, standing, sitting, and laying. Different machine learning algorithms were applied on this dataset for classification and their accuracy rates were compared. KNN and SVM were found to be the most accurate of all.

INDEX TERMS: decision tree, Human Activity Recognition (HAR), K-Nearest Neighbour (KNN), logistic regression, random forest, Support Vector Machine (SVM)image

I. INTRODUCTION

Today's smartphones are well-equipped with several sensors including motion detectors, such as accelerometer and gyroscope. Data generated by these motion sensors is used as input in different classification models. These models identify the type of activity in which the smartphone user is involved, for instance, walking, standing, walking upstairs, walking downstairs, and sitting.

In the recent past, the study of Human Activity Recognition (HAR) has gained popularity among researchers. With the right and precise information about users' activities, behaviors and interests, the scope of various applications can be further widened in different fields including medicine, security, entertainment, health, homecare systems, prisoner monitoring, physical therapy, and rehabilitation, among others.

HAR has been an active field of interest and research for almost a decade. It is mainly about analyzing user activities and interpreting the ongoing events accurately. Considerable efforts have been carried out to improve the user experience with mobile devices by improving their performance through high accuracy. Classification models play a vital role in it.

The main aim of HAR systems is to examine human activities and to interpret ongoing events, successfully. In this project, different classification algorithms were compared to find out which model worked best in HAR. The following five classification

models were selected for comparison:

i. Decision Trees
ii. K-Nearest Neighbour (KNN)
iii. Logistic Regression
iv. Support Vector Machine (SVM)
v. Random Forest

II. Related Work

Charlene and Nestor explained the basic HAR in smartphones. They proposed that recognition performance of gyroscope, accelerometer, and magnetometer. Sensor fusion was inspected to gain valuable insights on feature level. These insights assisted in data collection and dynamic sensing. Six activities namely, running, walking, standing, sitting, walking downstairs, and walking upstairs were incorporated from low sensor data. Data was gathered based on subjects and feature selection was carried out to optimize the resource use. In this study, KNN algorithm and decision tree were used for classification. The findings suggested that in contrast to decision tree, KNN is better in terms of performance[1].This paper compared the advantages and disadvantages of five algorithms, CNN, LSTM, BLSTM, MLP and SVM, in the recognition of human behavior [3].

Lara and Miguel collected data about HAR using wearable sensors. They surveyed and qualitatively compared twenty-eight systems with respect to the learning approach, response time, flexibility, obtrusiveness, and some other design issues. The basics of feature extraction and machine learning were also included because they are crucial for every HAR system. Lastly, numerous ideas were presented for future research to outspread as mentioned in [2].

This paper compared the advantages and disadvantages of five algorithms, CNN, LSTM, BLSTM, MLP and SVM, in the recognition of human behavior [3].

Modern smartphones and wearables often contain multiple embedded sensors which generate significant amounts of data. This information can be used for body monitoring-based areas such as healthcare, indoor location, user-adaptive recommendations and transportation [4].

This research proposed a CNN-LSTM approach to human activity recognition that seeks to improve the accuracy of activity recognition by leveraging the robustness in feature extraction of a CNN network while taking advantage of the work an LSTM model does for

time series forecasting and classification [5].
Smartphones increasingly becoming ubiquitous and being equipped with various sensors, nowadays, there is a trend towards implementing HAR (Human Activity Recognition) algorithms and applications on smartphones, including health monitoring, self-managing system and fitness tracking [6].
In this paper, convolutional layers are combined with long short-term memory (LSTM), along with the deep learning neural network for human activities recognition (HAR). The proposed model extracts the features in an automated way and categorizes them with some model attributes. In general, LSTM is an alternative form of recurrent neural network (RNN) which is famous for temporal sequences' processing [7].
Data annotation is a time-consuming process posing major limitations to the development of Human Activity Recognition (HAR) systems. The availability of a large amount of labeled data is required for supervised Machine Learning (ML) approaches, especially in the case of online and personalized approaches requiring user specific datasets to be labeled [8].
Powerful algorithms are required to analyze these heterogeneous and high-dimension streaming data efficiently. This paper proposes a novel fast and robust deep convolutional neural network structure (FR-DCNN) for human activity recognition (HAR) using a smartphone. It enhances the effectiveness and extends the information of the collected raw data from the inertial measurement unit (IMU) sensors by integrating a series of signal processing algorithms and a signal selection module. It enables a fast computational method for building the DCNN classifier by adding a data compression module [9].
Human Activity Recognition (HAR) can be defined as the automatic prediction of the regular human activities performed in our day-to-day life, such as walking, running, cooking, performing office work, etc[10].

III. DATA SET

The dataset used for this project was borrowed from UCI ML Repository. This HAR dataset was developed by taking the recordings of 30 participants while carrying out the actions of routine living (ARL), though holding an attached smartphone using implanted inertial sensors. Each person performed six

activities (walking, downstairs walking, upstairs walking, laying, standing, and sitting) while carrying a smartphone. This is done by using embedded gyroscope and accelerometer, which captured the angular velocity of 3-axial at a constant rate having 50Hz as linear acceleration of 3-axial.

This data set carried the following readings for each record:

- o The estimated body accelerometer and total acceleration as triaxial acceleration form.The angular (triaxial) velocity taken from the gyroscope.

o A feature vector with the frequency and time domain variable of 561.

IV. EXPLORATORY ANALYSIS

Data Preparation

Data set was split into two different files for training and testing data. Exploratory analysis was performed on the data set to understand the features and activities.

Training Data

Train(X) = train. data.drop (['Activity', 'subject'], Axis=1) train(Y) = train. Data ["Activity"]

Test Data

Test(X) = test.data.drop (['Activity', 'subject'],axis=1)

Test(Y) = test.data ["Activity"]

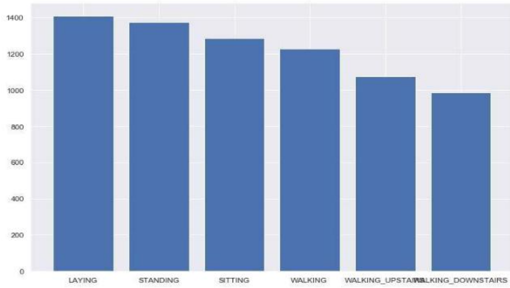

Fig.1. BAR CHART Activities Performed

Fig.2. Features Distribution

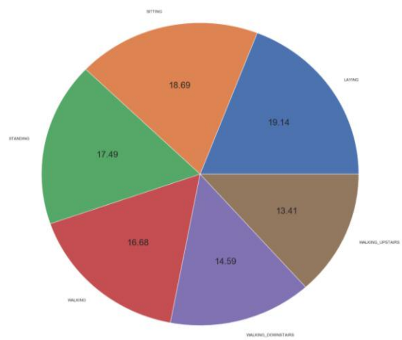

Fig. 3. Activities Performed by Percentage

From the above treatment of data, it is clear that all classes are of approximately same size. This

fact is important in order to ensure that the machine learning algorithms are not biased towards any one of the given classes.

V. METHODOLOGY

Machine learning methodologies were applied on the HAR dataset using different classification models - as explained below.

A. DECISION TREE

A decision tree is an appropriate representation model used for the classification of particular samples. It is a supervised machine learning approach in which the data is constantly split by approximating it to a definite parameter.

The decision tree algorithm was applied on training data with a depth of '8'. After fitting the model on the training set, the accuracy on test data (test.csv file) was found to be 88%, which is reasonably accurate.

For improving the accuracy, cross-validation method was also applied and the result was 87%, which is slightly lower than the original. Then, the data was split into three different portions: training (60%), validation (20%) and testing (20%). A new model was trained the model on split data. The scores of the model on validation data and test data were checked and their accuracy was found to be 94% - better than the initial model.

B. K-NEAREST NEIGHBOUR (KNN)

KNN classifies objects based on the closest sample from the training data. It is considered to be the simplest of all machine learning classification algorithms.

KNN was applied on the training data set and the n_neighbors to 10 after training. The accuracy of the test set was 90.6%.

Same splitting was repeated to apply on KNN, train, validate and test. After training the model, accuracy was improved to 96.6%

C. *LOGISTIC REGRESSION*

Logistic regression is a statistical learning method used in supervised machine learning. It is mostly used for classification tasks.

It was applied to the training set. After training the model, the score of the test data was 99%. However, logistics regression, by default, is limited to a two-class classification. Therefore, its results have not been incorporated in the final conclusion. Although some extensions, such as one vs others, can make logistic regression useful for solving multi-class classification problems, it is beyond the scope of this study.

D. SUPPORT VECTOR MACHINE (SVM)

Another very popular machine learning approach namely Support Vector Machine (SVM) finds a hyperplane in an N-dimensional space (N — the no. of features) that clearly categorizes the data points. SVM finds a hyperplane with a maximum margin, that is, the maximum distance among the data points of the classes.

SVM was applied on the training data. The hyper-parameters were set at C=1.0 and gamma = scale. After training the SVM model, the accuracy of the test set was 93%.

Repeating the same splitting to apply on SVM, train, validate and test. After training the model, a slight improvement was observed with an accuracy of 96.8%.

VI. RANDOM FOREST

It consists of a large number of individual decision trees that work as an ensemble. Each decision tree output in this classifier makes a class prediction. The class with the majority of votes serves as the prediction of the model.

After SVM, random forest was applied. The accuracy score of this model was significantly better (92%) as compared to the decision tree model.

VII. CONCLUSION

In this project, several machine learning algorithms were used to create predictive models for the classification of human activities based on the dataset obtained from smartphone sensors. Five different machine learning techniques were used for classification (KNN, logistic regression, decision tree, SVM, and random forest) and their accuracy rates were compared.

Overall, all models performed very well on this dataset. However, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) were found to have the highest accuracy among all, that is, 96.6% and 96.8%, respectively.

For future work, the same data can also be used to predict the subjects (people) as well as using the machine learning models to see the patterns of the sensory data of different people.

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